

ANALYZING EQUITY IN TRUCK-DRONE COOPERATIVE DELIVERY FOR RURAL AREAS

Henan (Beaty) Zhu

Department of Civil and Environmental Engineering
Rensselaer Polytechnic Institute
Troy, NY 12180, United States
zhuh18@rpi.edu

Xiaozheng (Sean) He, Ph.D., Corresponding Author

Department of Civil and Environmental Engineering
Rensselaer Polytechnic Institute
Troy, NY 12180, United States
hex6@rpi.edu

Ziping Wang, Ph.D.

Department of Information Science and Systems
Morgan State University
Baltimore, MD 21251, United States
ziping.wang@morgan.edu

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ABSTRACT

Given the surge in rural logistics services and the disparities between urban and rural delivery services, a compelling necessity emerges to explore innovative drone-based delivery solutions. The challenges inherent in truck-drone delivery due to technological and physical barriers affect service quality for some rural customers, thus magnifying concerns about delivery fairness. To investigate delivery equity, we present a truck-drone cooperative delivery model to analyze rural customers' accessibility to such innovative delivery technology. This model accommodates rural residents' delivery preferences while optimizing truck routes. Drones are dispatched from designated trucks to serve customers within their flight distance. Our proposed heuristic algorithm, founded on graph-based truck-drone delivery preferences, solves this intricate problem efficiently. Numerical experiments underscore the efficacy of our approach, highlighting substantial reductions in delivery costs and an impressive 20% increase in drone deliveries on a large-scale network. Through sensitivity analyses exploring drone operational costs and flight distances—affected by government policies and technological advancements—we devise an equity metric that gauges the efficiency and accessibility of rapid rural delivery services under the truck-drone delivery framework. Our research contributes to equity analysis, addressing challenges faced by logistics companies and rural residents. Moreover, it bridges the gap between urban and rural logistics, fostering an inclusive and equitable delivery ecosystem benefiting all customers, regardless of their location.

Keywords: Drone-Truck Cooperative Delivery, Equity, Rural Logistics, Vehicle Routing

1 INTRODUCTION

2 In the wake of the pandemic, there has been a substantial surge in online shopping, resulting in
3 heightened customer expectations for equitable and efficient delivery services. The growing trend
4 of online shopping not only stimulates economic recovery but also drives rapid expansion in the
5 logistics market. Urban logistics, equipped with advanced technologies, have been successful in
6 meeting the flourishing delivery demands. However, a sharp contrast emerges when we consider
7 rural logistics, which struggle to fulfill the same customer expectations due to limited accessibil-
8 ity and higher marginal delivery costs. Delivery trucks in rural areas often navigate circuitous
9 roads, leading to elevated fuel and labor expenses, while aging infrastructures and long-distance
10 routes further challenge the efficiency of rural delivery. As a result, rural residents face significant
11 disadvantages, encountering delivery journeys nearly twice as long as their urban counterparts (1).

12 The discrepancy between urban and rural delivery services underscores the compelling
13 need for innovative solutions to achieve delivery equity. Equity is a multifaceted concept explored
14 by researchers from various dimensions (2), such as spatial and social equity (3), accessibility eq-
15 uity (4, 5), technological equity (6, 7). Technological equity, from a temporal perspective, allows
16 for the evaluation of effects on innovation and technological changes (8). In the context of rural
17 delivery, some rural customers face limitations in accessing same-day delivery services due to lim-
18 ited delivery technology or physical barriers, however, their service could be significantly improved
19 with the deployment of advanced delivery drones. Companies like USPS (9) and Amazon(10) have
20 already begun adopting alternative delivery methods, such as truck delivery with drones, to reduce
21 costs and enhance efficiency for rural areas.

22 While embracing such cutting-edge technologies, we seek to foster technological equity,
23 ensuring that all regions have access to state-of-the-art delivery solutions. In this fast-evolving
24 landscape of online shopping, delivery companies must adopt cost-effective strategies to improve
25 efficiency and capacity in rural logistics systems. By prioritizing delivery equity, encompassing
26 technological equity, we can create a more inclusive and fair delivery ecosystem, benefiting every
27 customer regardless of their location. This approach not only bridges the gap between urban and
28 rural delivery services but also contributes to a more equitable and thriving logistics market overall.
29 As we continue to adapt to the escalating demands of the post-pandemic world, a commitment to
30 delivery equity remains central to achieving a fair and efficient distribution of goods and services
31 for all.

32 Building upon emerging technologies, the logistics industry is making remarkable strides
33 toward achieving efficient delivery. In particular, drone-assisted delivery has been explored and
34 tested, such as Amazon Prime Air service (10) in California and Walmart DroneUp service in
35 Texas and Arizona, U.S. (11). These innovative services benefit customers from efficient same-
36 day delivery, particularly in urban centers where drone delivery networks are rapidly expanding. It
37 is projected that by the end of 2023, the drone delivery network will cover 4 million U.S. house-
38 holds across six states and facilitate the delivery of over 1 million packages (11). The integration
39 of traditional truck delivery with drones holds the potential for significant economic profits and of-
40 fers a flexible delivery plan for large-scale logistic networks. The cooperation between trucks and
41 drones can enhance delivery efficiency and safety (12, 13). As such, these technological advance-
42 ments not only contribute to the rapid expansion of the logistics market but also lay a pathway to
43 ensure that cutting-edge delivery solutions are accessible to customers in diverse regions.

44 In the exploration of cutting-edge delivery solutions, the integration of trucks and drones
45 has gained substantial research attention across various scenarios. This truck-drone cooperative

delivery presents a promising approach to optimize delivery routes and reduce total completion time. Pioneering research on a single truck with multiple drones, such as the introduction of the truck-drone routing problem to the traveling salesman problem (VRPD) by Murray and Chu (14), paved the way for subsequent studies to expand the delivery scale with efficient models and fast algorithms (15–17). The complexity of the large-scale truck-drone cooperative delivery problem prompted further investigation, leading to the VRPDERO model by Schermer et al. (18). This model considers the possibility of en-route drone charging and introduces a hybrid variable neighborhood search (VNS) and tabu search approach, enabling the solution of large instances. Some researchers have explored the concept of multiple drones being carried by a single truck, simultaneously fulfilling delivery tasks along the truck's route to serve customers (19, 20). To address this complex scenario, exact algorithms like logic-based Benders decomposition have been designed. In addition to optimal routing, the consideration of time window demand for receiving goods has gained attention in the context of truck-drone delivery problems. Kuo et al. (21) proposed the vehicle routing problems with drones, taking time windows into account, and developed heuristic search algorithms to solve the proposed intricate models efficiently.

Other studies have investigated the impacts of technological advancements on truck-drone cooperative delivery services. The rapid advancements in drone technologies have significantly improved flight endurance and package load capacity, overcoming some of the initial limitations posed by maximum flight mileage and limited battery life (22). One advancement in truck-drone integration involves utilizing trucks to provide charging services for drones during delivery operations. Moreover, researchers have analyzed the possibilities of cooperative delivery with multiple trucks and multiple drones, recognizing the potential benefits in efficiency and customer satisfaction. However, as we explore this multi-dimensional approach to integrated delivery, new challenges emerge. The increased complexity of the problem, including computation time and solution scales, makes solving large-scale delivery scenarios more challenging (23). Researchers have attempted to tackle this obstacle by developing Mixed-Integer Linear Programming (MILP) models to optimize drone routes, considering the multi-drop condition for drones. Nevertheless, computation times can still be long, even for instances with a moderate number of customers.

To enhance efficiency, studies have further investigated the concept of multiple drones departing from and returning to a single truck after serving one or multiple customers, with the objective of minimizing the total arrival time of both trucks and drones (24, 25). The introduction of drone stations, where drones can launch and operate to deliver packages, further improves the potential of this approach (26). Trucks can travel to these stations and carry additional delivery drones to serve customers, optimizing the delivery process. While these innovative methods offer promising solutions for large-scale instances, they require truck drivers' attention to monitor changes in drone assignments (27). Ensuring seamless coordination between trucks and drones becomes essential to fully grasp the benefits of this integrated cooperative delivery approach.

The review of existing research on truck-drone integration reveals the crucial need to address the specific demands of rural logistics. Previous studies often overlooked the increasing importance of rural deliveries and the technical equity associated with the advancements of drone technologies. With the significant improvements in delivery drone capabilities, such as extended flight endurance and increased payload capacity, the potential for flexible multiple deliveries throughout the process becomes evident. In response to these challenges and opportunities, our focus lies in proposing a cooperative truck-drone delivery model and algorithm that can help us further analyze the technological equity and efficiency of delivery in large-scale rural applica-

tion scenarios. Moreover, we acknowledge the continuous developments in drone technologies, and our research aims to explore how these advancements can further enhance the collaboration between trucks and drones in the delivery process.

Our contributions are threefold. First, we study the rural truck-drone delivery problem, analyzing real-world rural logistic scenarios to gain insights into the unique challenges they present in rural areas. Second, in order to facilitate the analysis of technical equity and efficiency, we consider the requirements of truck-drone delivery and present a novel cooperative truck-drone delivery model and develop a graph-based truck-drone delivery algorithm. This algorithm is designed to find high-quality solutions, efficiently optimizing the proposed model to meet the diverse delivery demands of rural areas. Finally, to validate the effectiveness of our approach, we conduct computational experiments on both small and large scales, simulating actual rural networks. These experiments include comprehensive sensitivity analyses, allowing us to gain a deeper understanding of this complex delivery problem and refine our approach accordingly. By focusing on the specific requirements of rural logistics and integrating customer preferences into our cooperative truck-drone delivery model, we aim to contribute to a more equitable and efficient delivery ecosystem that caters to the diverse needs of customers across various regions.

THE TRUCK-DRONE COOPERATIVE DELIVERY MODEL AND ALGORITHM

In this section, we will focus on a truck-drone cooperative delivery problem for a remote rural area to support the analysis of the equity and efficiency of cooperative delivery, with the consideration of necessary delivery requirements and potential government incentives on the cooperative delivery costs. We first introduce the cooperative delivery problem description with the basic assumption and an illustrative example. We then propose the cooperative truck-drone delivery model suitable for analyzing rural area delivery. Finally, a heuristic algorithm is designed to solve the proposed model efficiently. The definitions of sets, parameters, and variables used are summarized into Table 1.

Problem Description

The truck-drone cooperative delivery problem in the rural transportation network could assign multiple trucks with drones to simultaneously finish delivery tasks along rural routes, as shown in Figure 1. For rural areas, the current delivery challenges stem from the rough road conditions and meandering paths required to reach remote delivery customers with limited accessibility. As a result, trucks must maintain a safe and slow travel speed along their long-distance routes to ensure effective delivery. Truck drivers have to spend more energy and time delivering packages door to door. Meanwhile, the increasing gas price also gradually causes high costs and much pressure on transport companies to manage rural delivery.

Drones have excellent advantages in overcoming these difficulties and saving delivery time, especially long-distance deliveries. In addition, the government can develop supportive policies to reduce the drone delivery cost c_d to encourage the drone-assisted cooperative delivery method, which can stimulate the innovation of the whole logistic market (28, 29). Thus, this paper aims to design an efficient cooperative truck-drone delivery method to release the delivery pressure and improve delivery efficiency in rural areas.

In the rural transportation network defined by graph $G = (V, A)$, trucks (K) and drones (D) jointly complete delivery tasks for all customer nodes (V^c). These trucks could travel along the actual road links (A) to deliver packages for some customer nodes served by trucks (V^T). Drones

TABLE 1: List of notations

Symbol	Description
Sets	
G	Network, $G = (V, A)$
V	Set of all nodes, $i, j \in V$
V^o	Set of all nodes except depot origin node $o(s)$
V^d	Set of all nodes except depot destination node $d(s)$
V^c	Set of customer nodes
V^T	Set of customer nodes served by trucks
V^D	Set of customer nodes served by drones
V_j^-	Set of preorder customer nodes before node j
V_j^+	Set of subsequent customer nodes after node j
A	Set of all links in the road network, $(i, j) \in A$
A^T	Set of links used by trucks, $(i, j) \in A^T$
A^D	Set of links used by drones, $(i, j) \in A^{D_0}$
S	Set of customer delivery weight, $s(i) \in S$
K	Set of trucks
D	Set of drones
Index	
$o(s)$	Depot origin node
$d(s)$	Depot destination node
i, j, k	Customer node
(i, j)	Link for drone or truck from node i to node j
Parameters	
c_k	Truck fuel cost per mile
c_d	Drone travel cost per mile
$l_{i,j}^T$	Path length traveled by trucks between node i and node j
$l_{i,j}^D$	Path length traveled by drones between node i and node j
N^c	Number of customer nodes
N^T	Number of trucks
N^D	Number of drones
F^D	Maximum flight mileage for each drone delivery
$s(i)$	Delivery weight for customer node i
W^T	Load weight limit for each truck
W^D	Load weight limit for each drone
R_i^D	Acceptance rate for drone delivery at customer node i
Variables	
$x_{i,j}$	1 if a truck traverses link (i, j) from node i to j ; otherwise, 0
$y_{i,j}$	1 if a drone traverses link (i, j) from node i to j ; otherwise, 0
$z_{i,j}$	Link load weight for truck link (i, j) from node i to j

- 1 could directly fly to other customer nodes served by drones (V^D) from one truck and finally return
- 2 to the same truck after delivering packages. Not all customers would like to afford extra fees
- 3 generated by drone delivery. Thus, we introduce the acceptance rate (R_i^D) of drone delivery to
- 4 verify the potential customers served by drones. Trucks must leave the depot departure node ($o(s)$)



FIGURE 1: Cooperative truck-drone delivery in rural areas

and return to the depot destination node ($d(s)$) after finishing all assigned delivery tasks. Each truck could load no more than 2 drones during delivery and provide the necessary charging facilities for drones. Besides, trucks and drones both have the upper limit of loading weight (W^T and W^D), which could help to sufficiently utilize the delivery resources and guarantee travel safety for all delivery routes.

The cooperative truck-drone delivery model aims to minimize the total generalized cost of truck and drone delivery and ensure effective drone and truck delivery routes in large-scale rural networks. An integer optimization model is proposed to satisfy the demand and make specific delivery plans for trucks and drones. And this paper designs a heuristic approach to solve the proposed optimization model.

Truck-drone Cooperative Delivery Model

Based on the actual rural transportation network, the cooperative delivery optimization model is proposed to minimize the total generalized delivery cost of required trucks and drones, and could satisfy necessary delivery constraints considering the rural delivery demand.

The objective function can be presented as follows.

$$\min Z = w_1 \sum_{(i,j) \in A^T} c_k \cdot x_{i,j} \cdot l_{i,j}^T + w_2 \sum_{(i,j) \in A^D} c_d \cdot y_{i,j} \cdot l_{i,j}^D \cdot (1 - R_i^D) \cdot (1 - R_j^D) \quad (1)$$

Subject to,

(1) **Delivery demand:** Customer delivery request constraint

$$\sum_{\substack{i \in V^o \\ i \neq j}} x_{i,j} + \sum_{\substack{i \in V^o \\ i \neq j}} y_{i,j} = 1 \quad \forall j \in V^c \quad (2)$$

(2) **Truck delivery response:** Truck delivery constraint for customer nodes served by trucks

$$\sum_{\substack{k \in V^o \\ k \neq i}} x_{k,i} = 1 \quad \forall i \in V^T \quad (3)$$

$$\sum_{\substack{j \in V^d \\ i \neq j}} x_{i,j} = 1 \quad \forall i \in V^T \quad (4)$$

(3) **Drone delivery response:** Drone delivery constraint for customer nodes served by drones

$$\sum_{\substack{k \in V^o \\ k \neq i}} y_{k,i} = 1 \quad \forall i \in V^D \quad (5)$$

$$\sum_{\substack{j \in V^d \\ i \neq j}} y_{i,j} = 1 \quad \forall i \in V^D \quad (6)$$

(4) **Truck supply:** The total amount of available trucks constraint

$$\sum_{j \in V^d} x_{o(s),j} = \sum_{k \in V^o} x_{k,d(s)} = N^T \quad (7)$$

(5) **Drone supply:** The total amount of available drones constraint

$$\sum_{i \in V^o} x_{i,d(s)} = \sum_{j \in V^d} x_{o(s),j} = N^D \quad (8)$$

(6) **Remove sub-tour:** Sub-tour elimination constraints for all journey of trucks and drones

$$\sum_{i \in V^c \cup o(s) \cup a(s)} x_{i,i} = 0 \quad (9)$$

$$\sum_{i \in V^c \cup o(s) \cup a(s)} y_{i,i} = 0 \quad (10)$$

$$x_{i,j} + x_{j,i} \leq 1 \quad \forall i, j \in V^c \quad (11)$$

$$y_{i,j} + y_{j,i} \leq 1 \quad \forall i, j \in V^c \quad (12)$$

(7) **Truck flow:** Truck flow balance constraint

$$\sum_{\substack{i \in V^o \\ i \neq j}} x_{i,j} = \sum_{\substack{k \in V^d \\ j \neq k}} x_{j,k} \quad \forall j \in V^c \quad (13)$$

(8) **Drone delivery order:** Drone delivery process constraint

$$\sum_{i \in V_j^-} y_{i,j} \leq 1 \quad \forall j \in V^D \quad (14)$$

$$\sum_{k \in V_j^+} y_{j,k} \leq 1 \quad \forall j \in V^D \quad (15)$$

(9) **Drone departure and return:** The relationship constraint between the truck and the assigned drones

$$y_{i,j} + y_{j,k} \leq \sum_{\substack{i \in V^o \\ m \neq i}} x_{m,i} + \sum_{\substack{k \in V^o \\ n \neq k}} x_{n,k} \quad \forall i, k \in V^c, j \in V^D \quad (16)$$

(10) **Truck delivery capacity:** The load weight constraints for trucks with drones along the routes

$$z_{i,j} \geq s(j) + \sum_{\substack{k \in V^T \\ j \neq k}} z_{j,k} + \sum_{\substack{u \in V^D \\ j \neq u}} y_{j,u} * s(u) + (x_{i,j} - 1) * M \quad \forall i, j \in V^T \quad (17)$$

$$z_{i,j} \leq W^T \quad \forall i, j \in V^T \quad (18)$$

(11) **Drone flight mileage:** The flight mileage constraint for drones

$$y_{i,j} l_{i,j}^T + y_{j,k} l_{j,k}^T \leq F^D \quad \forall i, k \in \{V^c \cup o(s) \cup d(s)\}, j \in V^D \quad (19)$$

(12) **Drone delivery capacity:** The load weight constraints for drones

$$s(i) \leq W^D \quad \forall i \in V^D \quad (20)$$

(13) **Decision variables:** Binary decision variables constraints

$$x_{i,j} \in \{0, 1\} \quad \forall i, j \in \{V^c \cup o(s) \cup d(s)\} \quad (21)$$

$$y_{i,j} \in \{0, 1\} \quad \forall i, j \in \{V^c \cup o(s) \cup d(s)\} \quad (22)$$

Constraint (2) ensures that each customer can receive the package by a drone or a truck. Constraints (3)-(4) ensure that certain customers can only be served by trucks. Constraints (5)-(6) ensure that some customer nodes can only be served by drones. Constraint (7) guarantees the utilization of trucks, limited to the number N^T of required trucks. Constraint (8) guarantees the utilization of drones, limited to the number N^D of required drones. Constraints (9)-(12) are sub-tour elimination constraints that ensure no sub-tours in the tours of trucks and drones. Constraint (13) ensures that the number of trucks entering a served node $j \in V^c$ equals the number of trucks leaving that node. Constraints (14)-(15) define the existence of a drone that can arrive at customer node j if it can be served by a drone and depart from node j to a subsequent node. Constraint (16) represents the ability of the drone to depart from and arrive at each stop of the trucks. Constraints (17)-(18) represent that the link load weight of each truck for the link (i, j) can handle the subsequent delivery weight by trucks and drone delivery weight after node j . Constraint (19) ensures that the drone flight mileage for each drone delivery is under the maximum flight mileage. Constraint (20) ensures that the delivery weight taken by a drone is under the load limit. The decision variables $x_{i,j}$ and $y_{i,j}$ are binary variables that indicate whether the truck (drone) will visit the arc (i, j) . This proposed model is a path-based integer optimization model for solving cooperative delivery routing problems for trucks and drones.

32 Solution Algorithm

In this section, we design a graph-based delivery preference algorithm for trucks and drones. Given the rural transportation network (G) , delivery locations, packages weight of customer nodes, the customer acceptance rate of drone delivery, and available trucks and drones, the proposed algorithm could first solve a potential delivery graph for drones (G_0^D) which considers the drone battery and load limits.

Then, the graph G_0^D needs to remove those customer nodes and adjacent links that customers strongly reject the delivery of drones, and update the drone delivery graph, including the feasible delivery nodes (V^D) and travel links (A^D). Based on the cooperative truck-drone delivery model, this heuristic algorithm could fulfill the efficient truck-drone delivery route design considering customer delivery preferences and fast solve the complex NP-hard optimization model. The

1 algorithm procedure is shown in the Algorithm 1.

Algorithm 1 Pseudo-code for the graph-based truck-drone delivery preference algorithm

Input: Rural transportation network (G), customer nodes and delivery weight, customer delivery preference, truck set K and drone set D

Output: Delivery routes for drones and trucks

Create an empty truck-delivery graph as $G^T = (V^T, A^T)$

Create an empty drone-delivery graph as $G_0^D = (V_0^D, A_0^D)$

for each node i in customer nodes V^c **do**

for each node j in customer nodes V^c **do**

if (direct link distance $<$ flight mileage F^D) and ((delivery weight at node $i <$ capacity W^D) or (delivery weight at node $j <$ capacity W^D)) **then**

 Add node i and j to V_0^D

 Add link (i, j) to A_0^D

 Update graph G_0^D

end if

end for

end for

for each node i in V_0^D **do**

if drone acceptance rate $R_i^D = 0$ **then**

 Remove node i from V_0^D

 Remove adjacent links from/to node i from A_0^D

 Update graph $G_0^D = (V_0^D, A_0^D)$

end if

end for

for each node i in customer nodes V^c **do**

if node i can only be served by a truck **then**

 Add node i to V^T for this truck

 Accumulate the delivery weight at node i into this truck

 Find the next delivery node for this truck

 Calculate the shortest path to the next delivery node

 Calculate the truck travel cost of this path

 Generate travel links into A^T for this truck

 Append these nodes and links into this truck route

end if

if node i can only be served by a drone **then**

if node i in V^D **then**

 Add node i to V^D for this drone

 Record the delivery weight at node i into this drone

 Find the departure and arrival node, and the corresponding truck for this drone delivery

 Generate travel links into A^D for this drone

 Calculate the drone travel cost under the customer preference

 Append these nodes and links into this drone route

end if

end if

if node i can be served by a truck or drone **then**

 Choose the best delivery method (truck or drone) based on all constraints and objective

 Calculate the travel cost for a truck or drone

 Append the calculated travel nodes and links to a truck or drone

end if

end for

1 COMPUTATIONAL EXPERIMENTS

2 In this section, we describe the numerical experiments in the actual rural transportation network.
 3 This section aims to evaluate the efficiency of the cooperative truck-drone delivery model and
 4 the proposed algorithm, and then analyze the cooperative delivery routes by different scale cases
 5 in actual rural transportation networks. Finally, we make the comprehensive sensitivity analysis
 6 to discuss the delivery equity and efficiency considering the long-term government incentives on
 7 drone delivery cost and the improvements in drone technology.

8 Experiment Overview

9 Using the OpenStreetMap and NEXTA (30) visualization platform, we generate the actual rural
 10 transportation network in Hereford, Maryland, United States. This large-scale rural network in-
 11 cludes 1625 road links and 758 nodes supporting local trucks and drone delivery. A delivery depot
 12 is located in the southernmost of the network, near a UPS Store. Specifically, this rural area has
 13 Gunpowder Falls, Genesee Valley Field, Prettyboy Dam, and some forest in the southwest corner
 14 of the whole network, which could be suitable for attempting innovative delivery methods with in-
 15 tegrated truck-drone delivery, and may save truck travel costs and travel time in the long-distance
 16 rural network. The experimental cases refer to the method in (23) to generate our problem in-
 17 stances auxiliary. Then, we randomly chose the customer nodes within this area and guaranteed
 18 enough customer demand around distant nature areas to testify our proposed model and algorithm
 19 better. The final selected customer nodes and large-scale rural network can be shown in Figure 2.
 20 The blue nodes and dark links denote the served customer location and road links, respectively.
 21 There are 242 customer nodes with delivery demand for the large-scale case and 101 customer
 22 nodes for the small case, and these customers are mainly distributed at the ends of the road and the
 23 gathering places of residential areas.

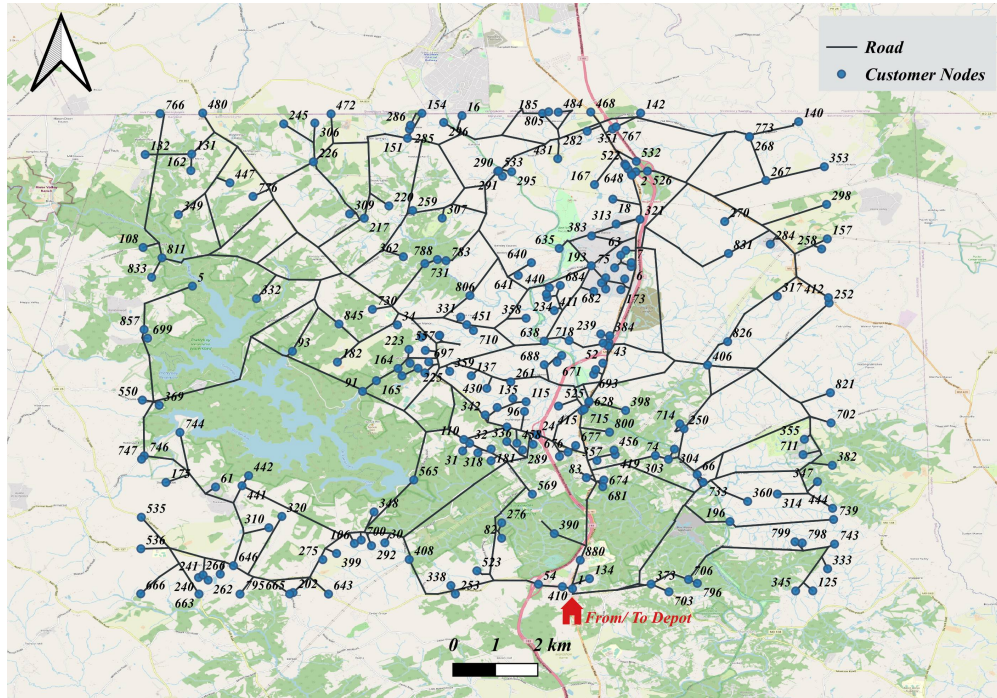


FIGURE 2: Large-scale rural delivery network in Hereford, MD, US

For the specific delivery weight of each customer location, we utilize the customer demand generation method of (23), and then assign various customer demands $s(i)$ which could satisfy the normal distribution with a mean 10 weight unit and standard deviation of 5 weight unit for those chosen customer locations. Similar to (23), we set the maximum load capacity of the trucks W^T and drones W^D are 1000 and 20 weight units, respectively.

For the cost of trucks and drones, the cost parameter of truck c_k is set to 0.34 \$/mile because fuel consumption is about 0.15 liter/km for a truck, and oil cost is about 1.33 \$/liter (31). The cost parameter of drone c_d is set to 0.05 \$/mile (32). The truck speed could be 30 mph in rural areas, and the drone speed is around 50 mph (33). The maximum drone flight time with a fully charged battery is around 30 minutes (34), and we could calculate the maximum flight mileage F^D as 10 miles. The proposed model and algorithm are solved by Python using Gurobi v9.1. All the computational experiments run on a desktop with Intel(R) Core (TM) i5-7500 CPU @ 3.40GHz.

Small Network Example

For illustrative purposes, the small-scale network is created with 101 nodes and 204 road links, as shown in Figure 3. The network surrounds a natural area. We assume that all nodes have delivery demand and the corresponding delivery weight for each customer node satisfying the normal distribution with a mean 10 weight unit and standard deviation of 5 weight units. The customer acceptance rate of drone delivery is assumed to satisfy the random Poisson distribution which the maximum value is less than 1.

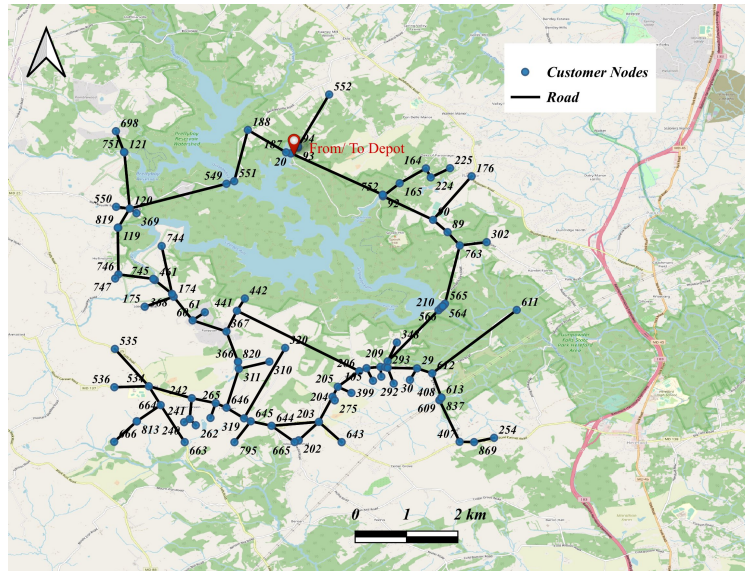
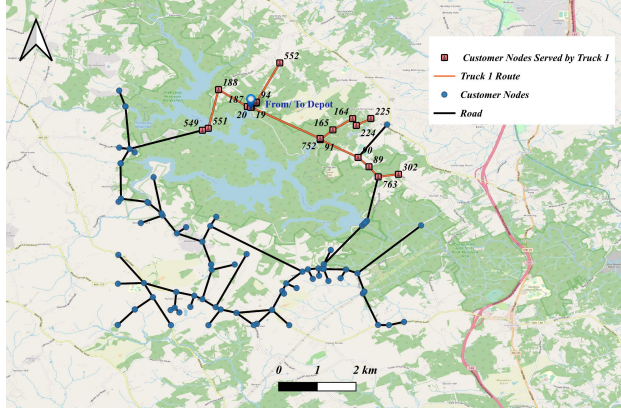


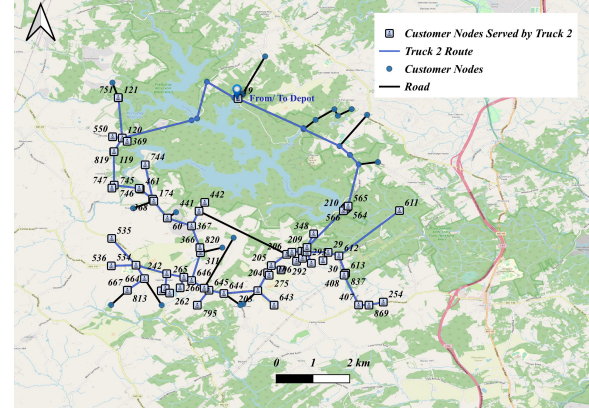
FIGURE 3: A small network in Hereford, MD, US

Based on the optimal results, we can obtain the 2 routes of trucks and the served customer nodes by trucks in Figure 4. In Figure 4, the orange (blue) rectangle nodes denote served customer locations by Truck 1 (Truck 2). The truck delivery trajectories, including the Truck 1 route and Truck 2 route, are composed of those orange (blue) links. All trucks start delivery from the depot node north of this network and return to the depot (Node 19) after these trucks finish all assigned delivery tasks. Although trucks could cover most areas, some detour trips are generated by trucks for some customer locations on the end of the road, such as customer locations near nature areas,

1 such as near dams, forests, and mountain valley locations. Note that each truck takes drones to
 2 collaboratively complete delivery tasks to save detour delivery time and fuel costs. We can find
 3 that Truck 1 serves those customers near the depot during short-distance delivery trips, and the
 4 other serves more customers surrounding natural areas with long-distance delivery trips.



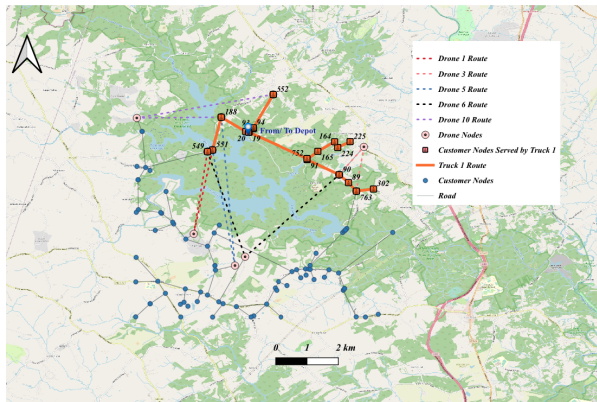
(a) Truck 1 route and served nodes



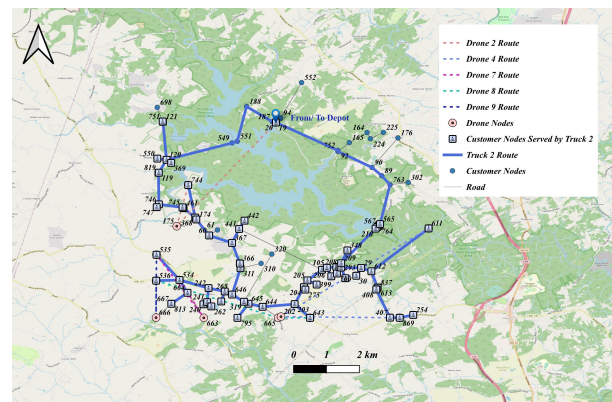
(b) Truck 2 route and served nodes

FIGURE 4: Truck delivery routes on the small network

5 Figure 5 shows the drone trajectory belonging to each truck, and served customer loca-
 6 tions. The pink nodes are served by customer nodes by drones, and the colorful dotted links are
 7 drone trajectories to deliver packages from/to trucks in this area. Drones can take off from the
 8 depot (Node 19) or trucks, and finally return to the depot or the truck they belong to during the
 9 limited battery. We could find that drones sometimes could fly through the natural area to finish
 10 delivery within their maximum one-way flight mileage. Thus, drone delivery could effectively and
 11 efficiently deliver packages into detour areas for trucks, and reduce the workload and delivery cost
 12 for truck drivers and companies.



(a) Drone trajectories belong to Truck 1



(b) Drone trajectories belong to Truck 2

FIGURE 5: Drone delivery trajectories on the small network

13 Table 2 shows the specific drone trajectory (includes each drone's origin, served node,
 14 and destination) and belonging truck ID. 10 delivery orders are finished by drones based on the

1 optimal results. The weight of packages delivered by drones remains within the acceptable range
 2 for drones. The average load of each drone is 14 weight units, and 47% of drones could carry
 3 packages between 15 and 20 weight units to the customer locations. The total delivery load of
 4 drones is 1215 weight units, which accounts for 12% of the total delivery demand in this rural
 5 area. Therefore, from the efficiency perspective, drones effectively deliver packages in rural areas
 6 and release the workload of truck delivery for residents' areas to some extent.

TABLE 2: Drone routes analysis for small case

Drone Delivery Order	Drone Trajectory	Truck ID
1	551, 61, 549	#1
2	19, 175, 744	#2
3	90, 176, 763	#1
4	869, 202, 611	#2
5	188, 310, 551	#1
6	549, 320, 90	#1
7	534, 663, 535	#2
8	536, 665, 643	#2
9	535, 666, 536	#2
10	552, 698, 188	#1

7 Finally, Figure 6 simultaneously shows the specific truck-drone delivery routes for this
 8 small network. The delivery routes could satisfy all customer demands well, and all trucks and
 9 drones depart from / return to the depot node, which guarantees the effectiveness of the proposed
 10 cooperative optimization model and algorithm design.

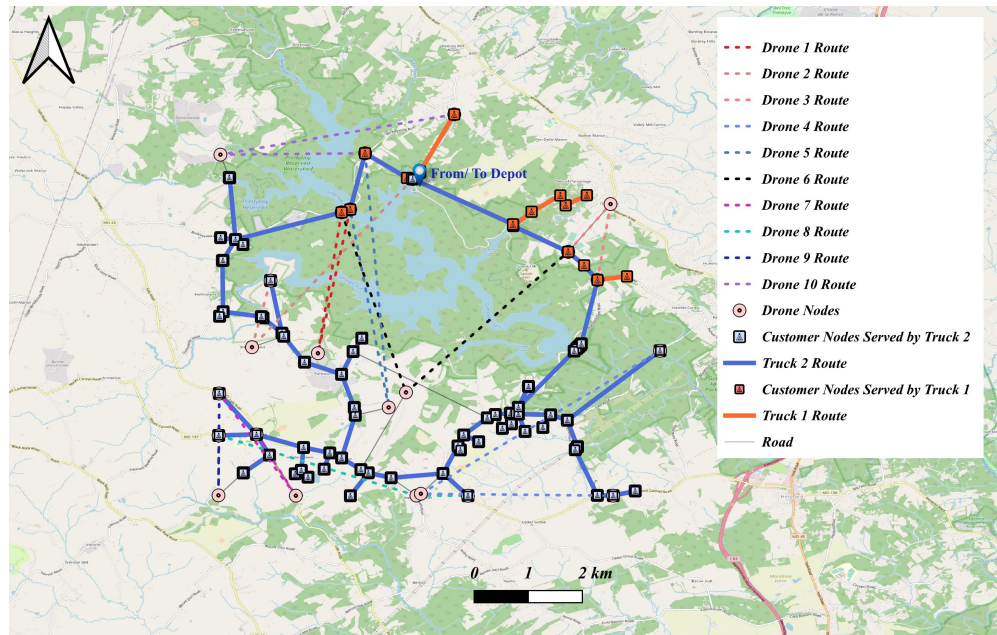


FIGURE 6: The cooperative truck-drone delivery trajectories on the small network

1 Large-Scale Network Example

2 This numerical experiment is conducted on the large-scale rural transportation network in Hereford, US, with 1625 road links and 758 nodes shown in Figure 2. The total number of selected customer nodes is 244, with a total delivery weight of 2510 units. There are 3 available trucks and 6 available drones belonging to these trucks.

6 For the large-scale case, we can obtain the truck delivery routes and served customer locations in Figure 7. Three truck routes and served customer nodes are presented in yellow, blue, and orange. Pink nodes are those customers served by drones, and adjacent purple links present the drone trajectories. All trucks start to deliver packages from the depot node (red mark) and return to the depot when trucks finish the assigned delivery tasks in this area.

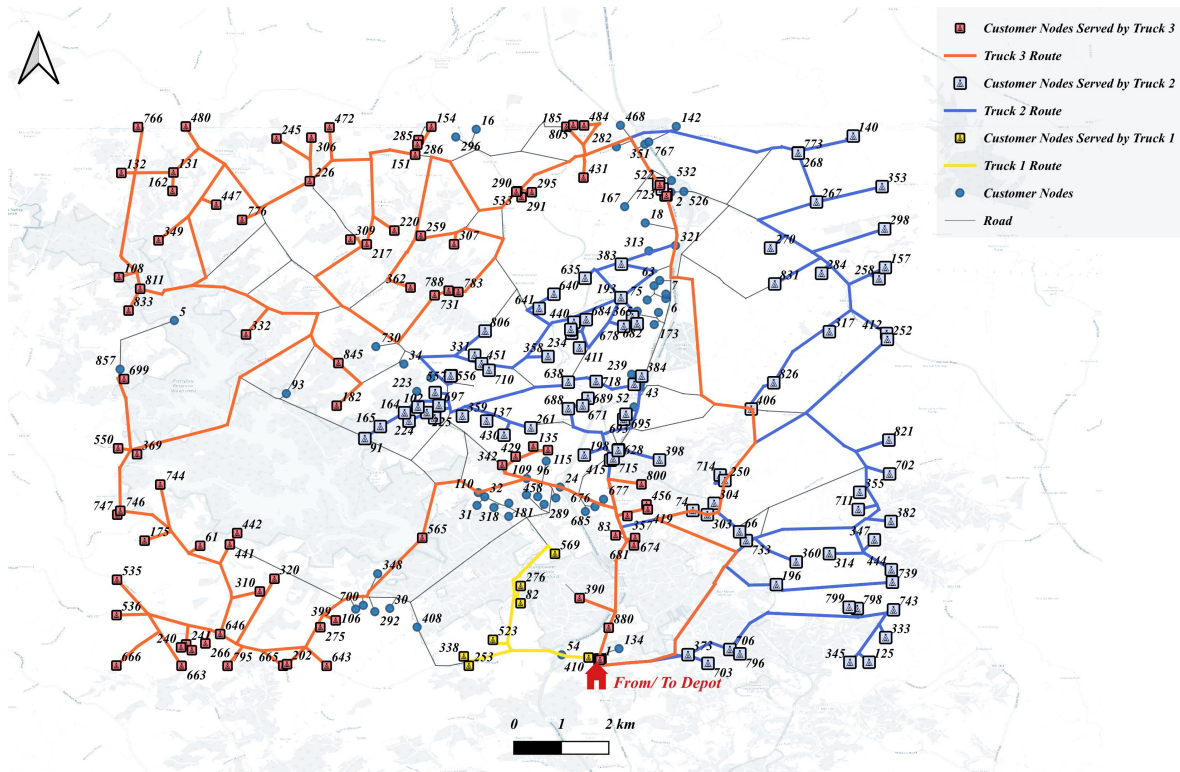
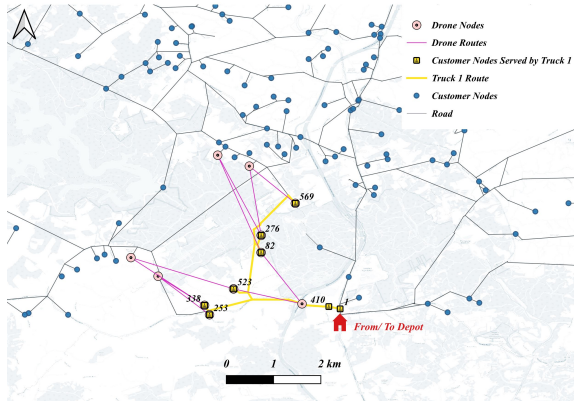


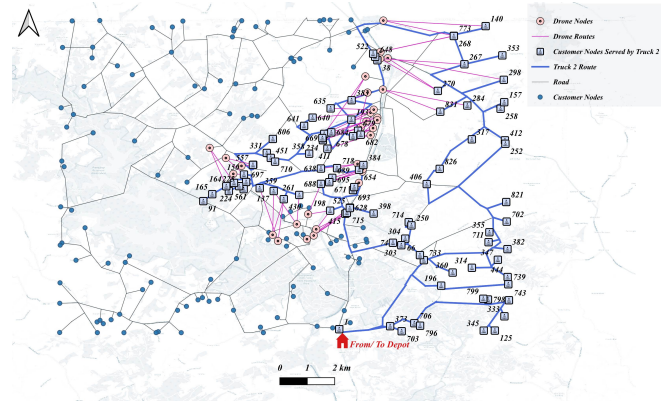
FIGURE 7: All truck routes and served nodes on a large-scale network

11 These trucks could serve many customer nodes successively within their load capacity and
 12 can deliver multiple packages to some detour scenarios, such as near dams, forests, and mountain
 13 valley locations. Meanwhile, the drones carried by each truck also deliver packages continuously
 14 and collaboratively finish all delivery tasks to satisfy transport demands for rural residents so as to
 15 save energy consumption in the whole logistics process. Figure 8 shows in detail three cooperative
 16 truck-drone delivery routes and served customer nodes along the delivery path. All carried drones
 17 can work well with the truck, whose flight trajectories closely follow the delivery path of the
 18 corresponding truck. This helps drivers quickly deliver packages to distant areas by drones, and it
 19 could be convenient to receive drones that complete delivery tasks along their path.

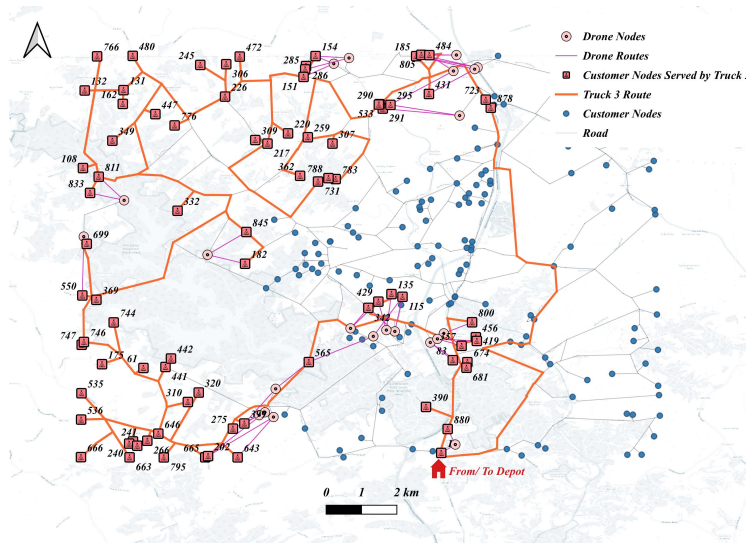
20 Then, this paper analyzes the truck and drone delivery results in Table 3, including the total
 21 delivery load of each truck and the carried drones, and the number of served customer nodes by



(a) Delivery routes and served nodes of Truck 1



(b) Delivery routes and served nodes of Truck 2 and carried drones



(c) Delivery routes and served nodes of Truck 3 and carried drones

FIGURE 8: Truck-drone cooperative delivery routes and served nodes on the largenetwork

1 truck and drone. Truck 2 and Truck 3 play important roles in truck delivery and mainly serve
 2 Hereford's eastern and western areas. Drones relieve truck1 delivery tasks by 28%, 24.4%, and
 3 27.5% tasks for Truck 2 and Truck 3, respectively. The delivery results could support the efficiency
 4 of the cooperative delivery method and reduce the generated delivery cost in the rural areas.

TABLE 3: Truck-drone delivery routes analysis for large-scale case

Truck ID	Total delivery load by truck	Number of served customers by truck	Total delivery load by drones	Number of served customers by drone
#1	85	8	33	5
#2	954	96	308	30
#3	819	83	311	22

1 All drone flight mileage of each round-trip is shown in Figure 9, including 57 delivery
 2 orders by drones. The total flight mileage of the drone is stable at 2.5 miles, and the maximum is
 3 no more than 4.5 miles, which is convenient for multiple flights and reduces charging times and
 4 flight costs.

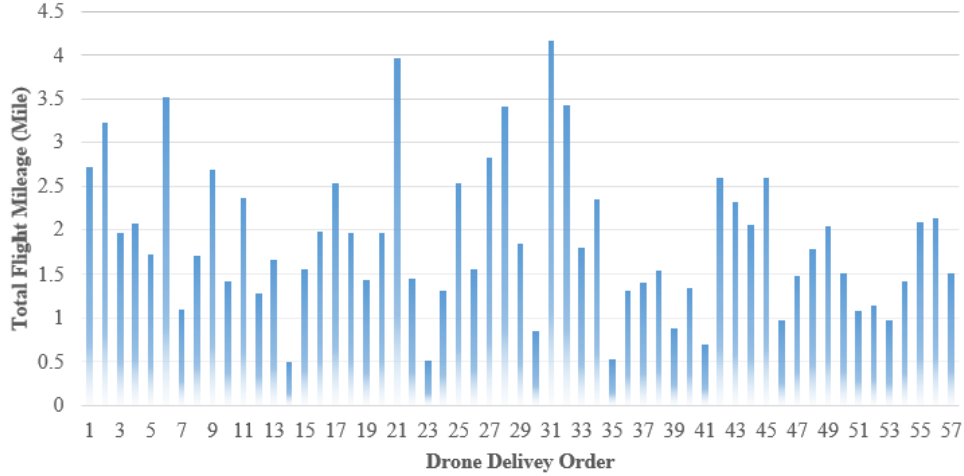


FIGURE 9: Drone total flight mileage for each delivery order

5 Finally, Figure 10 shows the complete truck-drone delivery routes, including three trucks
 6 and their carried drones in the large-scale rural network. It can be observed that all customer nodes
 7 are sufficiently served; trucks travel along the rural roads to finish their delivery tasks and can
 8 collaboratively deliver parts of packages with drones for customer nodes near nature areas. This
 9 could greatly improve transport efficiency and help to reduce the total delivery time and cost for
 10 truck drivers, especially for long-distance rural delivery scenarios.

11 Sensitivity Analysis on Drone Level for Large-scale Cases

12 In this section, we discuss the delivery equity and efficiency of the cooperative delivery, and con-
 13 duct the sensitivity analysis by changing the delivery cost of drone c_d and the maximum flight
 14 mileage F^D from the long-term development perspective.

15 When the drone endurance capabilities are improved, drones would take on longer-distance
 16 delivery tasks, and the delivery cost could be decreased by some governmental supportive policies
 17 to encourage the development of drone delivery. Thus, we classify four experimental scenar-
 18 ios based on the various drone technology(35) in Figure 11, considering two crucial dimensions:
 19 the efficiency and endurance of drones. The efficiency dimension denotes the delivery frequency
 20 of drones, and it could be improved with lower delivery costs. we use $\frac{1}{c_d}$ to represent this ef-
 21 ficiency dimension. The other dimension can be represented as drone endurance F^D . Scenario I
 22 presents the delivery instances using economic-level drones, which keep low delivery costs and
 23 short flight mileage. Scenario II utilizes advanced-level drones, which have expensive delivery
 24 costs and strong endurance abilities. Our large-scale case denotes the current scenario and still
 25 has promising space to improve the efficiency and endurance of drones. With the enhanced devel-
 26 opment of drone technology in the future, we consider futuristic-level drones to serve the logistic
 27 systems in Scenario III, which has both the economic delivery cost and strong endurance mileage.

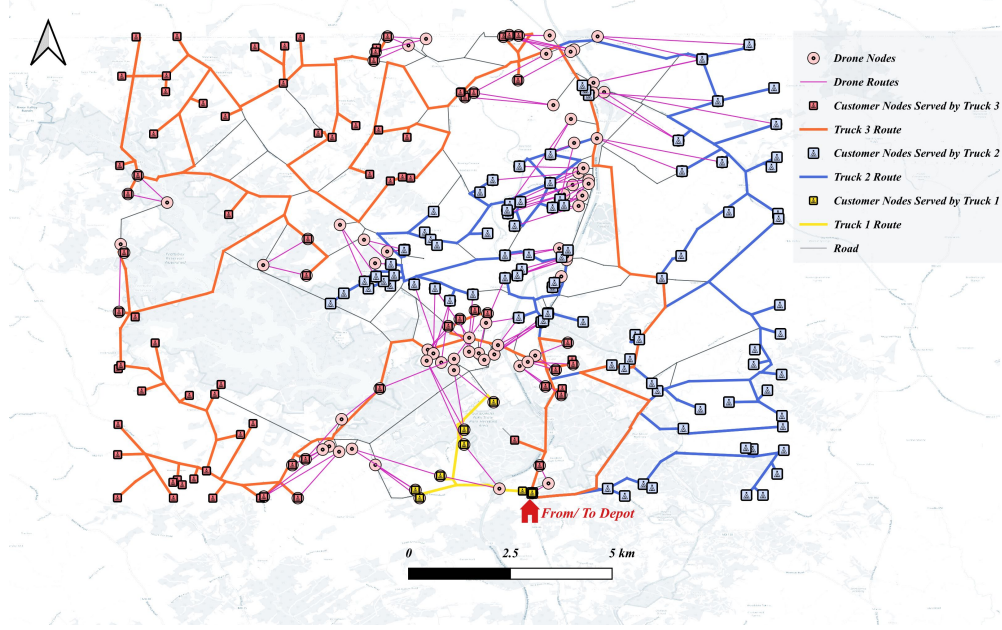


FIGURE 10: Truck-drone Cooperative delivery routes on the large network

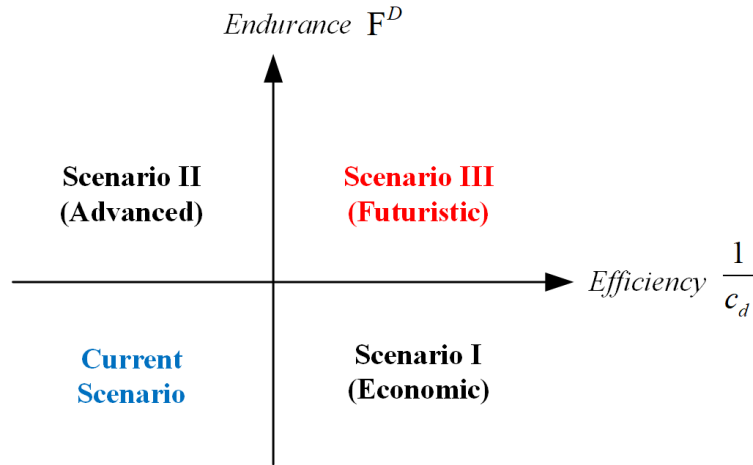


FIGURE 11: Experimental scenarios based on different drone technologies

1 Given the large-scale rural network, as this paper mentioned before, we test 7 experiments
 2 with various parameters of c_d and F^D and classify them as Scenario I, II, and III, respectively.
 3 We then experiment on these parameter combinations (c_d, F^D) to (0.04, 8), (0.03, 6), and (0.01,
 4 4) for scenario I, (0.07, 16), (0.06, 16) and (0.09, 25) for scenario II, (0.02, 12) for scenario III,
 5 respectively.

6 Table 4 illustrates the cooperative truck-drone delivery results based on three scenarios.
 7 For each experiment, we calculate the total load of delivery packages taken by each truck TD^T ,
 8 the total load of delivery packages taken by the carried drones TD^D , and the specific number of
 9 customers served by truck and carried drones, respectively. All cooperative delivery works well
 10 and collaborates to finish all delivery tasks in the large-scale rural logistic network.

TABLE 4: Cooperative delivery results on different drone scenarios

Instance	N^c	Scenario	c_d	F^D	Truck ID	TD^T	N^c served by truck	TD^D	N^c served by drone
1	242	I	0.04	8	#1	861	76	160	13
					#2	718	68	19	2
					#3	787	76	86	7
2	239		0.03	6	#1	758	69	99	8
					#2	694	69	41	3
					#3	872	79	115	11
3	240		0.01	4	#1	689	67	197	17
					#2	973	97	19	1
					#3	561	56	11	2
4	245	II	0.07	16	#1	372	37	31	3
					#2	828	88	170	18
					#3	893	94	59	5
5	238		0.06	16	#1	878	84	199	16
					#2	355	35	61	4
					#3	798	80	190	19
6	239		0.09	25	#1	977	95	39	3
					#2	547	51	18	4
					#3	829	81	70	5
7	242	III	0.02	12	#1	575	71	175	20
					#2	819	87	182	21
					#3	257	27	162	16

Next, we further analyze the equity performance and efficiency of cooperative delivery based on various drone scenarios. We introduce the evaluation indices, including the equity index, the average proportion of delivery weight taken by drones, and the acceptance rate of drone delivery. The equity index can be represented as “capability equality” (36–38). We utilize the ratio of the total delivery weight taken by drones to the total delivery weight taken by trucks in a specific rural logistic network. To ensure an alignment with the delivery service, it is imperative to design a suitable equity index tailored to its unique requirements and characteristics. This paper presents a new equity index e focusing on the percentage of package weights delivered by drones, which can be calculated by $TD^D/(TD^D + TD^T)$. This index takes into account the crucial role of delivery time savings in the rural delivery system. Using this index, we aim to measure the efficiency and accessibility of rapid delivery services in rural areas, such as Same Day Delivery. A higher equity index denotes a shorter average delivery time, leading to enhanced accessibility and convenience for residents in rural areas. The average proportion of delivery weight taken by drones can assess the operational efficiency of drones for package delivery. And the acceptance rate of drone delivery is utilized to evaluate the customer acceptance rate for diverse drone scenarios.

$$e = \frac{TD^D}{TD^T + TD^D} \quad (23)$$

Table 5 shows the results of evaluation indices for each instance. In Scenario I, the equity index is approximately 0.1 on average. Moreover, the drones' average proportion of delivery weight remains below 9.6%, and the customer acceptance rate for drone delivery is also lower than 9.2%. These findings indicate that economic-level drones are not suitable for long-distance rural logistic networks due to their limited endurance capability.

Although Scenario II uses advanced-level drone technology, these instances hardly come to the expected delivery performance based on the evaluation indices results. For those instances in Scenario II, instances 4 and 5 have the same maximum flight mileage of drones ($F^D = 16$), but their delivery costs are 0.07 \$/mile and 0.06 \$/mile, respectively. Since we consider the potential government incentives for drone delivery cost in the future, reduce the cost c_d in instance 5 to analyze the delivery equity and efficiency in the long term. Comparing these two instances, with the decreased delivery cost, the equity index has improved by approximately 0.07, the drones' average proportion of delivery weight comes to 17.5%, and the customer acceptance rate has also increased significantly, an increase of nearly 6%. We have observed that adopting a strategy to reduce the delivery costs of drones can significantly improve delivery equity and drone utilization, and facilitate the cooperative delivery process with trucks. Thus, the advanced-level drone scenarios need to find potential development policies to control the high delivery costs to stimulate drone delivery frequency and efficiency to attract rural logistic markets.

From the long-term perspective, instance 7 demonstrates a dual strategy of simultaneously reducing delivery costs and increasing drone endurance. As a result, the equity index reaches 0.24, with all other evaluation indices surpassing 23%. Overall, these instance results demonstrate that our approach is capable of accommodating futuristic delivery drones in the cooperative truck-drone delivery problem. Furthermore, our discussion offers valuable insights for the government in devising a development strategy for cooperative truck-drone delivery services in rural areas, shedding light on the types of drones that could gain favor in the rural logistics market.

TABLE 5: Performance analysis on different drone scenarios

Instance	Scenario	Equity Index	Average proportion of delivery weight taken by drones	Acceptance rate of drone delivery
1	I	0.10	9.4%	9.1%
2		0.10	9.6%	9.2%
3		0.09	8.7%	8.3%
4	II	0.11	10.3%	10.6%
5		0.18	17.5%	16.0%
6		0.05	4.9%	5.0%
7	III	0.24	26.7%	23.6%

CONCLUSIONS

In the wake of the thriving e-commerce economy, rural logistics networks face formidable challenges related to delivery cost and efficiency for both customers and companies. Innovative delivery methods, underpinned by effective optimization models and fast algorithms, can potentially spur the evolution of rural logistics, further reduce delivery costs and improve equity in rural ar-

1 eas. Moreover, the government agency might provide financial subsidies to help reduce delivery
2 costs and promote delivery equity in rural areas (39). Motivated by these dynamics, we propose
3 a truck-drone cooperative delivery model for real-world rural logistic scenarios. This model takes
4 into account the possible implications of advanced drone technology on cooperative delivery, in-
5 cluding enhancements in flight mileage, battery life, and load capacity, as well as rural customers'
6 acceptance rate of extra drone delivery costs.

7 The truck-drone cooperative delivery problem is modeled as a path-based integer program-
8 ming optimization model. A heuristic delivery algorithm based on network graphs and customer
9 preferences is developed to satisfy the customized delivery demand while improving computa-
10 tional efficiency for large-scale rural transportation networks. Based on the results of numerical
11 experiments, the validity of the proposed model and algorithm is demonstrated by efficient delivery
12 routes of trucks and drones and reduced delivery costs. Specifically, in actual rural scenarios, our
13 approach revealed that drone deliveries could alleviate 20% of each truck's delivery load and cur-
14 tail the number of detour trips made by delivery trucks on long-distance rural roads. Our numerical
15 experiments also show that effective government intervention, such as deploying subsidy policies
16 to reduce drone operation costs, can enhance the coverage and frequency of truck-drone coopera-
17 tive delivery services, and thus, improves the overall service equity and accessibility for customers.
18 These findings could provide valuable insights into resolving the stark conflicts between thriving
19 rural delivery demands and limited delivery resources.

20 In practice, the application of cooperative truck-drone deliveries needs to accommodate
21 more complex and diverse conditions, such as road network traffic congestion, weather, truck
22 driver working hours, and drone delivery accuracy. Moreover, rapidly advanced cutting-edge tech-
23 nologies may gradually reduce the currently high prices of these superior devices, driving delivery
24 innovation in large logistics markets. Future studies of the truck-drone delivery problem could fur-
25 ther consider these uncertain conditions, more detailed requirements, and potential advancements
26 in drone technologies.

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